Predicting Creativity in the Wild: Experience Sample and Sociometric Modeling of Teams

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ABSTRACT
Relationships between creativity in teamwork, and team members' movement and face-to-face interaction strength were investigated "in the wild" using sociometric badges (wearable sensors), electronic Experience Sampling Methods (ESM), the KEYS team creativity assessment instrument, and qualitative methods, in academic and industry settings. Activities (movement and face-to-face interaction) and creativity of one five-member and two seven-member teams were tracked for twenty-five days, eleven days, and fifteen days respectively. Paired-sample t-test confirmed average daily movement energy during creative days was significantly greater than on non-creative days and that face-to-face interaction tie strength of team members during creative days was significantly greater than for non-creative days. The combined approach of principal component analysis (PCA) and linear discriminant analysis (LDA) conducted on movement and face-to-face interaction data yielded a model that predicted creativity with 87.5% and 91% accuracy, respectively. Computational models that predict team creativity hold particular promise to enhance Creativity Support Tools.

Author Keywords
Creativity Support Tools (CST), Sociometric Modeling, Experience Sample Method, Wearable Computing.

ACM Classification Keywords
H.5.3 Group and Organization Interfaces

General Terms
Human Factors; Measurement.

INTRODUCTION
Understanding how to foster creative capacity is among the most important goals of our society in preparation for the future. While there are many definitions of creativity, there is broad consensus that creativity is the creation of anything that is useful and original [32]. Creativity takes place through the unfolding of moment-to-moment activities in natural environments. This investigation studies the relationship between group activity characterized through team members' movement and face-to-face interactions within teams, and creativity in research and development teams in industry and academia. Group activity was tracked through sensor data from sociometric badges [25]. A social science survey instrument KEYS [2][5] was implemented through electronic ESM and Day Reconstruction Method [21] to capture self-reported creativity and was supplemented with expert-coded creativity measures. Statistical methods, machine learning, and qualitative approaches were used to analyze and validate the relationship between group activity (movement and face-to-face interaction) and everyday creative and non-creative events. This investigation contributes to the basic science of creativity and to the empirical methodologies that assess creativity. Providing movement and face-to-face interactions as a means of continuously sensing creativity accurately, with minimal human input, this research contribute to the design of CST.

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Three studies ranging in duration from two to four weeks were conducted over a two-year period in leading research and development laboratories. These laboratories had similar spatial environments, consisting of a room with cubicles facing walls and a central collaboration space. All participants had regular working hours and the environment encouraged hands-on, real time interaction towards development of artifacts. To explore initial variables of interest, a pilot study was conducted with five participants over 25 days. Encouraged by the trends discovered in the pilot study, two further experiments were conducted with two, seven member teams, for 11 and 15 days, respectively.

The framework based on these studies paves the way for automated CST based on team activity [47] [48]. This framework combines existing qualitative methods of studying group creativity in context [4] with sensor-based data. The research was conducted in natural work place settings and advances the use of sensor data to support human creativity and teamwork.

BACKGROUND

Assessment of Creativity
Aimed at measuring creativity, several divergent thinking tests have been designed that test for fluency or rate of ideation in individuals. Some early tests proposed to test creativity were Guilford's Structure of Intellect (SOI) divergent production tests [19], and Torrance's Tests of

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Creative Thinking (TTCT) [51]. A limitation of these parametric approaches is that they may measure only one aspect of creativity and may only work in controlled laboratory conditions. Alternate approaches have focused on the creative qualities of the process and outcome or final products, e.g., the creative product semantic scale [8] and Amabile's consensual assessment technique (CAT) [2].

CAT can be employed to address domain specific creativity and also be extended for analysis of team creativity. CAT relies on the inter-rater reliability between these expert judges to evaluate levels of creativity in processes and products. Amabile has also developed the KEYS scale based on her componential model of creativity [3] [5] that measures a variety of factors such as affect, rewards, and motivation, and asks the participants to self report on creativity (on a Likert scale) and to explain what they did throughout the day in an open ended question format. This scale addresses individual, team, and context variables concurrently, with checks and cross checks to ensure consistency and accuracy of responses.

Group Creativity Research

Work on creativity has largely focused on individual creativity. However, in recent years, there has been an increased interest in studying team creativity within organizations. An important observation is that it is not very clear how individual creativity is linked to team creativity [43]. Researchers have often dealt with this conundrum by focusing on individual creativity alone, or on team creativity alone, or on processes of interactions between team members [6][43][48][50].

Group creativity can be conceived as an additive or disjunctive property of individual creativity [43]. If it is additive, then each individual member's creativity adds up to the final creative output of the team. If it is disjunctive, the most creative ideas which may come from one or more individuals are adopted by the team. Team creativity may also manifest itself as a weighted combination of individual contributions. Amabile, in her componential model of creativity, has pointed out that intra-individual factors such as organization incentive for innovation, resources made available, and external pressure can impact individual creativity [2]. Taggar [50] found that in addition to creativity relevant skills, domain relevant knowledge, and intrinsic motivation at the individual level, there might be group related processes that are relevant to creativity. Amabile's KEYS scale [5] quantifies such variables in a reliable manner suitable for measuring team creativity.

Sensors for feedback and the display of group behavior [13][25] have provided automated support for group performance. These tools employ sensors in laboratory environments and focus on single modality, such as speech [28]. Several CSTs have also been developed that aim to improve group creativity. Most of the studies in CSTs center on the comparisons of an experimental group that uses the CST system versus a nominal group (set of individuals not acting as a group) or a control group that does not use the system [31]. Studies tend to focus on quantifying interactions and using them as a measure of creativity and productivity.

Interactions and Movement in Group Creativity

Network communication strength and the types of communication modalities within a team are additional behavioral factors that may impact group creativity [26]. While there is a belief that face-to-face interaction strength is central to the understanding of social networks in relation to creativity, there is insufficient empirical evidence to indicate strong relationship between face-to-face interaction and creativity. Tie strength (weak, strong) is a function of the amount and quality of interactions, emotional intensity, and reciprocity that takes place between two individuals [17]. Zhou *et al.* [55] found that employees exhibited greater creativity when their number of weak ties was neither too low, nor too high (an intermediate level exhibited greatest level of creativity). Perry-Smith and Shalley [42] showed that weak ties rather than strong ties are beneficial for creativity among research scientists. In contrast, Obstfeld [34] showed that engineers with strong ties are more creative. These studies show a complex, inconclusive, and possibly domain specific relationship between tie strength and creativity.

Research has also investigated the nature of the structure of social networks, within teams, that is most supportive for creativity [35]. Burt [10] claims that a network with several structural holes (many disconnected individuals) may be more creative. Burt hypothesizes that members who are closer to these structural holes are exposed to a greater diversity of perspectives, which has a positive impact on creativity. On the other hand, Perry-Smith and Shalley [42] claim that a dense network with all members strongly connected to each other provides an opportunity for free interchange of information and hence greater creativity.

Most research conducted on the relationship between movement and creativity is in the exercise sciences where brief period of activity such as walking on the treadmill is followed by creativity assessment questionnaires [30][49]. These studies have established that physical activity in humans is linked to their creativity. However, research is needed to understand how individual movement in the work environment is related to creative production.

Sensor Based Approach to Group Creativity Research

Recent advancements in sensor based pattern recognition with applications such as face recognition [53] and gait recognition [27] demonstrate the power of detecting low level signal streams and recognizing relevant patterns from them. Sociometric badges [39], used to capture movement, speech, and location, are an interesting recent example. They are a form of "environmentally aware computing" allowing capture of person's location, presence, and

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elements of the environment [38]. HCI research has leveraged such sensors using speech, and artifacts to study interactions within members of groups [13][16][37].

Burleson et al.; Choudhary; Kapoor et al.; Kim et al.; Olguin-Olguin et al.; and Pentland [9][11][22][25][37] [41] have conducted empirical studies that use physiological sensing and wearable computing to understand and predict high level behavioral constructs such as affect, activity and creative output. Methods from affective computing have been able to distinguish affective state with 81% accuracy throughout everyday activities [22] while machine learning tools that incorporate Human Eigen behaviors and Coupled Hidden Markov Models (CHMMs) have been shown to account for 96% of the variance of behavior of typical individuals [15].

Assumptions and Challenges in Analyzing Group Data

Group research is a challenging task [45]. The most difficult challenge from a statistical perspective lies in analyzing data from groups [20][24]. Data gathered from individual participants in group studies is often interdependent, which limits the use of several statistical tools for analysis. Yet, employing many of these techniques can be valid in group analysis as long as observations are shown to be independent. A foremost technique to show independence is correlation analysis [20] [12][19][23][33]. In the investigations reported here, calculation of intraclass coefficients confirmed the assumption of independence of data to be valid.

INSTRUMENTS AND METHODS

The following instruments and methods were approved by Institutional Review [52].

Sociometric badges: wearable sensors, worn as a pendant around the neck, recorded network data (Infra Red pings) at 17 Hz, body movements (2D accelerometer) at 50 Hz and ambient audio, not used in the present studies, using embedded speaker at 8 kHz. Badges track location and analyze elements of participant's social interaction through bi-directional infrared transceiver, accelerometer, and low-resolution microphone analysis. No personally identifiable data is recorded which ensures privacy of subjects. The raw data from the sensors are extracted into meaningful features that may correlate with team members' characteristics. Badges are equipped with triaxial accelerometers that give the value of movement in X, Y, and Z directions. The mean and standard deviation of movement energy for each participant for each day was calculated. Movement energy gives a measure of the intensity of individual movement that includes the effect of variation in signal around the three axes in the accelerometer [37]. It may also be classified into various types of physical activity such as walking, running, and sleeping [44].

Calculating Face-To-Face Tie Strength: Infrared signals in the sociometric badges provide a measure of face-to-face interaction. Badges record presence and duration of other badges when they are in direct line of each other (IR signal cone of height ≤ 1 meter and radius $r \leq h \tan \Theta$ where $\Theta = \pm 15^{o}$) [37]. We counted the number of pings for each badge and constructed adjacency matrix for the data. Cells in the adjacency matrix represent the number of pings recorded for each badge with all other badges. This matrix was first made symmetric with respect to the minimum number of pings recorded for each pair. Subsequently, the adjacency matrix was used to generate face-to-face tie strength for each day (Total pings/Detected Number of Badges) for each participant. The badges have been extensively validated over several studies [7][25][40][37].

KEYS Scale: was used to obtain daily measures of creativity. The KEYS survey is designed to assess the perceived stimulants and obstacles to creativity in organizational work environments. Items of KEYS scale address negative and positive aspects of the environment. It is widely recognized as the current standard for measuring team creativity and innovation within organizational work environments [4]. The survey has fifteen questions, two of which are open-ended responses. A 7 point Likert scale is used for each of the questions. One measure is self-rated creativity that is extracted from the report of team creativity. The variable assesses member reports of creativity being experienced by the team. For the open ended questions, participants were asked to 1) "In a few words, briefly describe the major work you did on the assigned project pertaining to this study today, or the major activities you engaged in that were relevant to the target project" 2) "Briefly describe ONE event from today that stands out in your mind as relevant to the target project, your feelings about this project, your work on this project, your team's feelings about this project, or your team's work on this project."

CODE	EVENTS	CREATIVE (1/0)
11_P6_D4	Work on Cholecystectomy [sic] scene. Made a minor breakthrough today. A physics asset of a gall bladder model seemed to interact well. I pursued that lead with Cord and as it turned out I managed to create with his help a very nicely interacting model of the gall bladder.	1
12_P6_D4	Besides this I spent the day adding another layer to the connective tissue.	0

Table 1. A sample of coding combined narratives from events. CODE value represents Event Number_ParticipantID_Day. Note: This participant previously described adding the layer to connective tissue as a routine task.

KEYS requires an expert judge to rate the participants' reports by assigning numerical value for the level of creativity (0 or 1) in addition to the self-reports through the questionnaire. It has been shown to be reliable when the rating is conducted with one or more expert judges. Expert is defined as a person knowledgeable about domain.

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In this investigation, the method described by Amabile et al. [4] was followed to obtain "expert coded creativity." The descriptions from the open-ended questions were combined together to form open-ended narratives for each participant. Unique instances of completed actions were extracted from the narrative for each participant to identify individual 'events.' The KEYS coding protocol defines creative thought as any of the following: (1) a discovery, insight, or idea; (2) the act of searching for a discovery, insight, or idea; (3) solving a problem in a non-rote way; or (4) the act of searching for a problem solution in a non-rote way. Events that had any of these were labeled 1 and events that did not have any of these were labeled 0. Table 1 illustrates the process through an example.

The basic assumption of KEYS is that psychological perceptions of work environment by the team members play a vital role in their creativity. The underlying model [1] identifies three components within the individual that have an effect on creativity, including individual's intrinsic motivation, his or her thinking style, and domain-relevant knowledge. The KEYS scales have been validated over several studies and are reported to have high validity and reliability [2].

EXPLORATORY EXPERIMENT

A pilot study explored whether there are correlations between individual activity and self-reported team creativity in a small group. A combination of quantitative and qualitative data for a team of individuals over an extended period of time was collected. These individuals worked in an industry research environment that required high levels of information technology and creativity in an industry setting. Creativity was measured through an online survey that had a combination of scale-rated responses and open-ended questions that allowed participants to describe their day-to-day experience of creativity. A multi-methodological approach was used to explore the relationship between data obtained from the sensed activity (movement and face-to-face interaction) [39] and levels of creativity collected via electronic ESM [4]. The results of this study informed our hypotheses for subsequent experiments.

Participants: A team of five people (2 females, 3 males; mean age = 32.4 years, range= 26-38 years) participated in a five-week study (total 25 working days). All participants had undergraduate degrees in engineering and two had post-graduate degrees (1 MBA and 1 MS). The team was involved in software coding and research in a leading industrial research and development laboratory in the United States. All participants were part of a single team engaged in highly creative research and development activities. The participants were selected because they worked in a tightly knit single location laboratory advancing IT research. The members conduct the majority of work in this laboratory in a highly interactive manner. No rewards were given to participants in this study. The head of this department was contacted via email and they in turn put the experimenter in contact with the team that volunteered for the study. All participation was voluntary and participants had the option to opt out at any time.

Materials and Procedure: This study used sociometric badges and the KEYS daily questionnaire. The study was conducted at a remote site with a team involved professionally in software coding projects. The experimenter shipped the badges to the remote site at the beginning of the study. Participants were required to charge the badge on their own every night by plugging them into computers via a USB cable that was provided.

All participants were informed that the investigation was on workflow issues in teamwork. This was largely done to avoid any bias on the part of the participants towards creativity. All participants were given a unique participation ID through which they corresponded for the duration of the study. The participants were also informed that their responses would remain anonymous and evaluated by researchers unaffiliated with their work environment. The participants were ensured that the data would not be shared with the supervisors directly and only anonymized aggregate analysis would be presented to audiences.

Before the experiment began, subjects were requested to answer an initial demographic questionnaire. During the study, each subject wore a sociometric badge. The subjects were requested to wear the badges throughout their workday (9 am to 5 pm) during the experimental period. At the end of the day, subjects were requested to answer a daily questionnaire. The data collection protocol occurred for 25 days and provided us with an extensive sampling of creative, non-creative episodes and the activity profiles associated with it. A reminder was sent at 4:15 pm everyday with the survey link via email to each participant. The data was downloaded only once at the end of the study when the badges were shipped back. Except for initial clarification on how badges worked and debriefing, there was no interaction between the experimenter and the participants.

Data Analysis and Results

KEYS and Sociometric Badges data were analyzed.

KEYS Daily Questionnaire Data: While there are 15 questions in the KEYS survey, this analysis focused on three questions that dealt with self-rated creativity, expert-coded creativity, and measures of team interaction (other variables in the KEYS survey are beyond the scope of current investigation). Out of 125 expected responses (25 days *5 participants), 96 daily surveys were received, and the average response rate was 76.8% with a standard deviation of 23%. From the surveys, the value for self reported creativity was obtained (Likert Scale: 1 – 'not at

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all', 7 – 'extremely'). In addition to the scaled responses, the KEYS instrument and its methodology provide the opportunity for expert coding of creative and non-creative events. For each survey response, the narratives from the two open ended questions were combined. The participants' combined narratives ranged from 462 words to 2348 words with a mean of 53 words per entry.

Sociometric Badges Data: The five badges were collected at the end of the 25-day period. While the mean and standard deviation for four participants was obtained over all days successfully, one of the badges failed to record any data and the remaining four failed to record face-to-face interaction data. Due to the remote nature of the study and the lack of time stamps, the exact time and duration of wearing and taking off the badges could not be determined.

Correlation Results: Pearson correlation coefficient values obtained for all major variables. The significance value was set at 0.1 as this was an exploratory study with a low N. There was a significant large correlation ($r = 0.91$) between self-rated creativity and movement of the participants. There was a significant medium correlation ($r=0.77$) between speech and expert-coded creativity. There was a significant correlation ($r=0.88$) between degree (KEYS scale) and expert-coded creativity. There was a significant negative correlation ($r = -0.82$) between movement and hours spent with team (KEYS scale).

Summary: Participants' self-rated creativity was highly correlated with their daily movement energy. There was low correlation between expert-coded creativity and movement and between expert-coded creativity and self-reported creativity. The number of people a team member meets had medium correlation with expert-coded creativity. The data indicated a few interesting trends. First, participants feel more creative when they move more. Second, they are generally more creative when they are meeting more people in the team and feel more connected.

MAIN EXPERIMENT I

Experiment I employed the pilot study methodologies and procedures to investigate the following two hypotheses:

- **H1.** *Average daily movement energy of team members during days with above average self-rated creativity is significantly greater than the average daily movement of days with below average self-rated creativity*
- **H2.** *Average face-to-face tie strength of team members during days with above average expert-coded creativity is significantly greater than the average face-to-face tie strength of team members of days with below average expert-coded creativity*

with $p < 0.05$ accepted as statistically significant.

Methods

Seven participants engaged in creative research were observed for two work weeks (11 days) during regular work hours (9 am to 5 pm). The mean age of participants was 24.7 years (range = 24–32 years), and 4 out of 7 participants were men. The sample was highly educated, 4 out of 7 participants were college graduates engaged in postgraduate work, and 3 were senior undergraduates. All participants were recruited via email and signed consent form for voluntary participation prior to the start of the study. Approval was also obtained from the laboratory head, prior to the start of the study. No rewards were provided for participation in the study. Recruited participants worked together as a team in a Carnegie Research I University in information technology rich environments. For 11 days, the experimenter visited the laboratory each morning to ensure that the participants' badges were worn at 9 am. The experimenter observed activities throughout the day and at 5 pm requested the participants to turn the badges off.

Data Analysis and Results

KEYS Daily Questionnaire Data: Out of total 77 (11 days *7 people) daily online surveys, the number of surveys completed was 58. The mean response rate was 75% with a standard deviation of 19%. From the survey, the value of self-rated creativity was calculated. Expert-coded creativity scores were obtained by analyzing the narratives. Participants' combined narratives ranged from 63 words to 516 words with a mean of 290 words for each participant.

Sociometric Badge Data: For each day, participants' movement energies were calculated and face-to-face interaction recorded. The adjacency matrix thus obtained was made symmetric with respect to the lowest number of signals (or pings) that were recorded. The average number of pings was calculated for each participant for each day.

Experimental Data: The following four variables: (1) self-rated creativity; (2) expert-coded creativity; (3) movement energy; and (4) face-to-face tie strength were analyzed. The creativity data was mean split in two ways based on 1) self-rated creativity and 2) expert-coded creativity. K-Means clustering showed that the ratio of inter-cluster distance to intra-cluster distance was high ($R=0.94$) which validated the choice of mean split. For each of these two measures of creativity, the days that had values for creativity higher than the mean were labeled creative while those days that were at or below the mean value were classified as non-creative.

H1 Result: A paired-samples t-test was conducted to test H1. This t-test [$t(36) = 3.132$, $p < 0.005$] confirmed, the hypothesis that average daily movement energy during days with above average creativity ($M = 1.31$, $SD = 0.04$) was significantly greater than the average daily movement of days with below average creativity ($M = 1.29$, $SD = 0.03$). The eta-squared statistic (0.21) indicated a large effect size.

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H2 Result: A paired-samples t-test was conducted to test H2. The t test [t (21) = 1.05, p > 0.1] showed no significant difference between average face-to-face tie strength of team members during days with above average expert-coded creativity (M = 9.4, SD = 10) and the average face-to-face tie strength of team members (M = 6.3, SD = 7) for days with below average expert-coded creativity

Correlation Data: There was a significant correlation between face-to-face interaction and both self-rated creativity (r=0.45) and expert-coded creativity (r=0.45). A significant correlation (r=0.66) was also found between movement and self-rated creativity.

Summary: Results confirm H1, average movement for creative days is significantly higher than for non-creative days. H2 was not confirmed. Face-to-face interaction was highly correlated with expert-coded creativity and movement was highly correlated with self-rated creativity.

MAIN EXPERIMENT II

Experiment II built on results from Experiment I, using the same methodologies, procedures, and hypotheses.

Seven participants engaged in creative research were observed for two work weeks (15 days) during regular work hours (10 am -5 pm). They engaged in research intensive creative work in an information technology (IT) rich environment. The mean age of participants was 27.4 years (range = 23–32 years) and 6 out of 7 participants were men. Our sample was highly educated, 4 out of 7 participants were college graduates engaged in postgraduate work, and 3 were senior undergraduates. All participants were recruited via email and signed consent forms for voluntary participation prior to the start of the study. Approval was also obtained from the laboratory head prior to the study and no rewards were provided for participation.

Materials and Procedure: Experiment II followed Experiment I protocols, adding ESM reports to understand face-to-face interaction relationships with creativity. At the end of each hour (from 11 am - 5 pm), participants received an SMS request: "For the last hour, you were Creative 1 or Non-creative 2 and Meeting 1 or not meeting 2 (respond 1 1 if creative and meeting and so on)". Qualitative observations by an expert coder provided descriptions of events, people involved, actions, movement, and meetings.

Data Analysis and Results

KEYS Daily Questionnaire Data: Out of a total of 105 (15*7) daily surveys, the number of surveys completed was 76. The open-ended narratives were coded to obtain scores for expert-coded creativity for all participants for each of the 15 days. Participants' combined narratives ranged from 293 words to 1663 words with a mean of 973 words.

Sociometric Badge Data: Accelerometer data from the badge of each participant was downloaded every day. By using the same formula used in our previous studies, we calculated a movement energy array that was later used to give us mean and standard deviation of movement energy for each day. The average face-to-face tie strength was calculated for each participant across 15 days.

Experimental Data: We obtained the following four variables for each participant for 15 days: (1) self-rated creativity (2) expert-coded creativity (3) movement energy (4) average face-to-face tie strength. The data was mean split in two ways based on 1) self-rated creativity and 2) expert-coded creativity. For each of these two measures of creativity, the days that had values for creativity higher than the mean were labeled creative while those days at or below the mean value were classified as non-creative.

H1 Result. A paired-samples t test was conducted to test H1. The t test [t (23) = 6.49, p < 0.001] confirmed that average daily movement energy during days with above average self-rated creativity (M = 1.37, SD = 0.07) is significantly greater than the average daily movement of days with below average self-rated creativity (M = 1.24, SD = 0.09). This was a large effect (eta-squared = 0.36).

H2 Result. A paired-samples t test was conducted to test H2. The t test [t (41) = 2.36, p < 0.01] showed average face-to-face tie strength of team members during days with above average expert-coded creativity (M = 2.69, SD = 4.01) is significantly greater than the average face-to-face tie strength of team members for days with below average expert-coded creativity (M = 0.9, SD = 2.1). The eta-squared statistic (0.11) indicated a large effect size.

Correlation Data: Pearson product-moment correlations between all major variables in the study were calculated. Self-rated creativity was weakly, but significantly correlated with expert-coded creativity (r = 0.25). In addition, movement and self-rated creativity were significantly correlated (r = 0.55). Face-to-face interaction had significant correlation with both self-rated creativity (r = 0.20) and expert-coded creativity (r = 0.25).

SMS Data: A total 99 hours of data was collected for 1 hour intervals of self-reported daily activity indicating whether meetings or non-meetings were occurring and whether or not these hours were creative. We summed across all days for four variables: (1) Creative and Meeting (2) Creative and Not meeting (3) Non-creative and Meeting and (4) Non-creative and Not meeting. We found that people reported to be creative while they were meeting (165 hours) more than twice than when they reported to be not creative while meeting (71 hours). The correlation between self-rated creativity and creative and meeting reports was significant (r = 0.82, p<0.01), and there was significant negative correlation between reports of non-creative and non-meeting and self-rated creativity (r= -0.58, p<0.05).

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Summary: A significant difference was found between team member movements for creative days and non-creative days. Creative days were also shown to have higher face-to-face interaction than the non-creative days. Participants' SMS reports indicated that episodes of meeting one or more team members were twice as likely to be creative than non-creative. Moreover, across fifteen days, there was a significant correlation between meeting episodes and self-reported creativity. People were two times more likely to report non-creative events when not in meetings. Overall, results show that participants in a small group are likely to be more creative when they are more active, in terms of both movement and face-to-face interaction.

COMPUTATIONAL MODELING OF TEAM CREATIVITY

Statistical learning techniques and pattern recognition techniques on a validated subset of features available from the sociometric badges and labeled events were employed for the development of the computational models, following methods developed by Olguin et al. [36][37]. Olguin-Olguin et al. [37] have developed computational techniques for studying the relation between activity measured through sociometric badges and several variables like performance in healthcare environment and studying productivity in IT domains. These techniques employ signal processing techniques to extract relevant features from the data stream that correlate with social signals and measures of performance. Pentland employed eigenvector representation to study the variance of behavior of individuals [39]. They showed that there was limited amount of behavior variance across days for individuals implying high predictability.

With data from Experiments I and II, standard linear regression [14] was used to study relationships between activity-network profiles and the creativity class. Subsequently, Naïve Bayesian Classifier (NBC) [14] were employed. A third approach, a combination of principal component analysis (PCA) [14] for dimensionality reduction and linear discriminant analysis (LDA) [14] for classification based on approaches developed for face recognition by Li et al. [29], was then used to develop a deterministic approach to computational modeling of creativity. Maximum Likelihood Estimation (MLE) was used as the training approach. Matlab 2009® algorithm implementations, *glmfit* for linear regression, NaiveBayes.fit and predict for NBC and classify function for LDA, were used.

Procedure for Computational Modeling Approaches

Data from Experiments I and II provided day-to-day team members' activity and overall creativity scores. The data sets were combined and the days were divided into two classes: creative and non-creative based on the mean split of reported creativity measures. The movement data was divided based on self-rated creativity while the face-to-face interaction (or network pings) data was divided based on expert-coded creativity. The corresponding measures were chosen to classify the data based on the results from Experiments I and II. Overall 182 hours of data per subject (participant N=7, for 26 days) totaling 1274 hours of data was collected. The activity as measured through accelerometer (X, Y, and Z) and network pings from IR were considered for analysis.

For face-to-face quantification, the average IR ping information for the day for each participant was considered for the computational model. As each experiment had 7 participants, there was 7x7 matrix of face-to-face network pings as sensed by the IR sensor for each day. For every day, the frequency of pings for every pair of participants, which could be understood as network edge strength in the team's network, was calculated. In the team network, participants are the node and the edges represent face-to-face interactions. Of the 26 days worth of network data, 14 were labeled creative and 12 were labeled as non-creative according to expert-coded creativity. The 7x7 matrix of IR ping frequency for each day was linearized into a 49x1 vector representing pings per day for all possible person-person interactions. The creativity class (creative or non-creative) for each vector was known. This matrix was employed to train pattern recognition algorithms to assess expert-coded creativity, measure in Experiment I and II.

For movement analysis, the accelerometer readings were sampled at 50,000 readings per day with 3 measures per reading (X,Y,Z), to define a representative sample of activity profile for each day. The day-activity matrix was assembled by linearizing the accelerometer activity into a vector and then assembling the individual vectors into a matrix. For each vector, a class of creativity (creative or non-creative) was known. This matrix was employed to train pattern recognition algorithms to assess creativity.

For each of the three approaches, an 80/20 train/test paradigm was employed. Algorithms for movement data and network ping (face-to-face interaction) data were trained individually as they provided related but distinct information and related to different measures of creativity. In the analysis of face-to-face interactions, the core idea was to classify the entire day as being creative or non-creative for the whole team. This computational engine was tuned to gestalt creativity classification for an entire day and hence provided complementary information to the movement data based classifier that provided per-day per-person ratings. The network ping based classifier was geared towards assessing the team's everyday creativity.

Results from Computational Modeling Approaches

PCA was applied for dimensionality reduction and LDA for classification as a means of achieving high accuracy and fast computation results. The energy of the eigenvalues indicated 7 dimensions were sufficient to cover 95% of variance with the movement data; PCA was used to reduce

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the dimensionality of the data from 150,000 to 7. LDA was then used as the classification technique. In the case of face-to-face interaction strength, 3 dimensions were sufficient to represent 95% of variance in PCA, hence dimensionality was reduced to 3 and LDA was performed.

For movement data, linear regression showed the lowest classification accuracy of 45.2%; the fit was not high or significant. NBC showed an accuracy of 70.2%. The NBC fit performed significantly better than linear regression achieving accuracies of about 70% for both movement and face-to-face interaction data. The combined approach of PCA and LDA showed an accuracy of 87.5% for per-day per-person data as measured through the movement stream and 90.9% for face-to-face interaction.

Additional endeavors (see [52]) using reduced dimensionality data for linear regression and NBC showed slight improvements (47.1% and 71% classification accuracy). This suggests the superiority of the PCA/LDA approach in obtaining accurate classification. The results for face-to-face interaction data were analogous, with the PCA/LDA combination achieving the highest recognition accuracy of 90.9%, NBC achieving 71.2% and linear regression achieving an accuracy of 44.5%.

Discussion of Computational Modeling Approaches

While the results are based on a limited data set and require further validation, it is encouraging to note that computational engines can be designed to ascertain creativity from sensor data. PCA and LDA analysis yielded close to 92% accuracy. While we cannot imply causality to this result, the fact that linear approaches give encouraging results opens up several possibilities for analysis of creativity in an automated fashion. The two approaches NBC and PCA-LDA combination both have unique advantages and requirements. NBC can be very successful in developing long-term trends and patterns and can be employed in a formative fashion. The PCA-LDA combination can actually give the highest accuracy as it removes noise from the original data. Noise may have contributed to low accuracy in the results of linear regression. We trained on data from two studies, suggesting this approach may be somewhat robust and generalizable.

DISCUSSION

This investigation shows there is a significant relationship between (1) individual movement and self-rated creativity and (2) face-to-face interaction and expert-coded creativity.

Specifically, daily movement energy for creative days was significantly higher than the movement energy of the non-creative days for team members. In terms of face-to-face interaction, in Experiment I, while no significant difference between face-to-face interaction for creative and noncreative days classified on the basis of expert-coded creativity was found, the trend in significance encouraged further exploration in Experiment II, using sms based ESM to gather participants report on their ongoing behavior [54]. Participants reported the highest number of both creative and meeting and noncreative and not-meeting episodes. The third highest number was creative and not-meeting. The least reported variable was not creative and meeting. This suggests that participants were generally more creative when they were meeting and generally more non-creative when they were not meeting. However, an important component of overall team creativity is a combination of team and individual creativity. Reports of being creative and not-meeting tend to be on the same days participants had also reported to be creative and meeting. Teams were far more creative on days in which the members met. Team members also reported to be personally more creative after active interactions with other team members. In Experiment II, face-to-face tie strength was significantly greater in the creative days than that of non-creative days.

These results show a strong correlation between movement and self-rated creativity. Prior studies have found that exercise or a physical activity of some kind enhances cognitive performance [49] and physical activity is correlated with creativity [30]. While the results of these prior studies were based on questionnaire data implemented on the middle aged or elderly populations, the presented research is the first effort of its kind to employ a multi-methodological approach that confirms the relationship between sensed movement data with creativity.

In the KEYS scale, there are two variables namely individual creativity and team creativity. Interestingly, there was 94% correlation between reported scores of team creativity and individual creativity. This might be because individual participants had no prior definition of creativity or basis of differentiating between the two variables. This raises the question, "What, exactly, do the personal creativity and team creativity variables represent in the KEYS scale?" The results show that how participants feel about their own creativity (self-reported personal creativity) may be the same as how they rate their team as being creative (team creativity). It must be noted that the creativity score obtained by an expert that is based on their descriptions is not necessarily correlated with their creativity self-reports. This could be because these measure two different facets of creativity.

Several key questions need to be answered with respect to the nature of the following question: how much and how often team interactions should occur for the team to be more creative? To provide clues to some of these questions, the role of degree (number of team members meeting each other) in both the experiments was explored and found in both cases to have no significant [$t\ (36) = 1.55, p > 0.12$; $t\ (20) = 0.23, p > 0.8$]. The means in the two cases in both the experiments were almost equivalent (Non Creative: M = 1.81, SD = 1.68; M = 1.67, SD = 1.8; Creative: M = 1.24, SD = 1.38; M = 1.52, SD = 1.5). Thus it is not the

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number of people a team member meets with, but rather the quality of face-to-face interaction (or the time spent with the team members) that influences creativity.

The computational modeling results show the feasibility of developing an automated system for creativity based on team members' activities. Linear regression analysis did not yield high accuracy but the Bayesian modeling and the combined PCA and LDA approach had high recognition accuracies. Principal component analysis showed that 7 dimensions encompassed close to 95% variation in the underlying data from movement data and 3 dimensions encompassed 95% variation in the face-to-face interaction data. The analysis of principal dimensions and the weights of the individual units showed that individuals with highest creativity were given the highest weight and individuals with the lowest creativity where given the lowest weight.

CONCLUSION

Computational modeling of team creativity has several benefits: (1) it allows automated evaluation and prediction of creativity; (2) it paves the way for software and programs that support creativity; (3) it allows development of guidelines and procedures towards creativity in teams and within organizations; (4) it enhances theoretical understandings of creativity and its relationship to team member activity.

The key findings of these studies were: (1) days in which the team is highly creative are also the days in which the teams' members meet more often, and (2) days in which team members report to be highly creative have higher levels of movement among team members than the days they report to be non-creative. Through a multi-methodological approach that coupled sensor based analysis, wearable computing, and creative behavior assessment this investigation helps us better understand the nature and mechanisms of team creativity in the wild.

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